



Research Paper

An Exploratory Study Using an Artificial Neural Network to Predict Fatigue from Mobile Phone Use: A Population-Based Survey in Algeria

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ABSTRACT

Background: Mobile phones are widely used, raising questions about the possible health effects of the radiofrequency electromagnetic fields they emit. Fatigue is frequently reported in this context, but it is influenced by multiple, interacting factors that are difficult to model with classical statistical methods. Artificial neural networks (ANNs) may help explore these complex relationships.

Methods: An ANN model was developed to estimate fatigue associated with cell phone use. Data were collected via a semi-structured questionnaire completed by 478 Algerian participants. The survey recorded sociodemographic data and patterns of mobile phone use. The network had a 5-10-1 architecture, and its performance was evaluated by mean squared error (MSE) and the coefficient of determination (R^2). A simple MATLAB interface was created to allow user input and display model outputs with a colour-coded indicator.

Results: The ANN achieved an MSE of 0.5993, indicating that it reproduced some general patterns in the data. However, the coefficient of determination was low ($R^2 = 0.0338$), showing that only a small proportion of the variability in fatigue scores was explained and that individual predictions were imprecise.

Conclusion: This exploratory study suggests that ANN-based models are feasible for analysing fatigue associated with mobile phone use, but the findings should be regarded as preliminary and are subject to some limitations. Larger, more diverse samples and richer, preferably objective, exposure and health measures will be required before such tools can be used for reliable risk assessment or public health guidance.

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Introduction

Mobile phone use has increased to levels never seen before worldwide. As these devices have become part of daily life, questions have also grown about the possible public health effects of exposure to radiofrequency electromagnetic fields (RF-EMFs) [1, 2]. The spread of RF-emitting sources such as mobile phones, base stations, and Wi-Fi access points has changed how and how often people are exposed. However, population-level exposure remains poorly described, and the relative contribution of each source remains uncertain [1]. The International Agency for Research on Cancer (IARC) has classified RF-EMFs as “Group 2B – possibly carcinogenic to humans” [3]. Experimental studies suggest that RFs may influence cellular processes, brain activity, and immune responses, and children may be particularly vulnerable [2].

Systematic reviews by major health agencies have not established a clear causal link between everyday RF-EMF exposure and adverse health outcomes. However, such exposure has been associated with self-reported symptoms including fatigue, memory impairment, hypertension, infertility, sleep disorders, and certain tumours [2, 4-7]. Fatigue is one of the most frequently reported complaints, particularly in heavy mobile phone users [8, 9].

Traditionally, studies investigating the relationship between mobile phone exposure and health outcomes have relied on statistical models such as linear or logistic regression. These approaches are commonly used to assess associations between exposure variables (e.g., daily phone call duration) and self-reported outcomes (e.g., fatigue). However, fatigue related to wireless technology use results from a complex, non-linear, and multifactorial interplay of sociodemographic and exposure factors, which classical statistical models may not adequately capture [9, 10]. This reliance on linear models constitutes a major knowledge gap, as it remains unclear whether more flexible, non-linear approaches could better capture these complex relationships. In contrast, artificial neural networks (ANNs) offer a more flexible approach, as they can learn hidden, non-linear relationships directly from the data [11-16]. Inspired by the functioning of the human brain, ANNs have already shown their usefulness in biomedical applications, particularly for disease prediction [13, 16].

To address this gap, the present study develops an ANN model to predict fatigue related to cell phone

use in an Algerian population. The model is based on five input variables: age, gender, duration of phone ownership, daily phone use duration, and the distance of the phone from the body during sleep. Using these variables, the ANN estimates the level of perceived fatigue and helps identify which factors contribute most strongly to its variation. Such information may support targeted prevention strategies and better guidance for mobile phone use in daily life. To the best of our knowledge, no previous study has used an ANN to model fatigue associated with cell phone use.

Materials and Methods

Data Collection

This study was conducted in Algeria with participants exposed to RF emissions from mobile phones. A semi-structured questionnaire was used, given to a randomly selected sample. The sample included people of different ages and both genders to ensure broad sociodemographic representation.

Before taking part, all participants were informed about the study's aims and provided written consent. Also, the research adhered to the ethical principles outlined in the Declaration of Helsinki. All responses were anonymized to protect participant confidentiality, and data were stored securely [17]. In total, 478 individuals from 48 wilayas (provinces) took part in the survey (Figure 1).

The questionnaire used in this study was developed based on a literature review of the potential effects of RF exposure. It was initially pilot-tested with a sample of 20 individuals to assess the clarity of the questions, the relevance of the wording, and the adequacy of the response options. The psychometric properties of the instrument were then evaluated. The Cronbach's alpha coefficient obtained was 0.819, indicating good internal consistency among the items and a reliability considered satisfactory for research purposes. On this basis, the intrinsic validity index was 0.905, suggesting a high degree of internal validity and allowing reasonable confidence in the results derived from this measurement tool.

For the neural network model, the input variables were: age (in years), gender (male or female), years of mobile phone ownership (< 1 year; 2–5 years; 6–10 years; > 10 years), average daily call duration (< 1 hour; 1–2 hours; 3–4 hours; 5–8 hours; > 8 hours), and mobile phone proximity during sleep (under the pillow; 0.1–0.5 m; 0.5–1 m; > 1 m away).

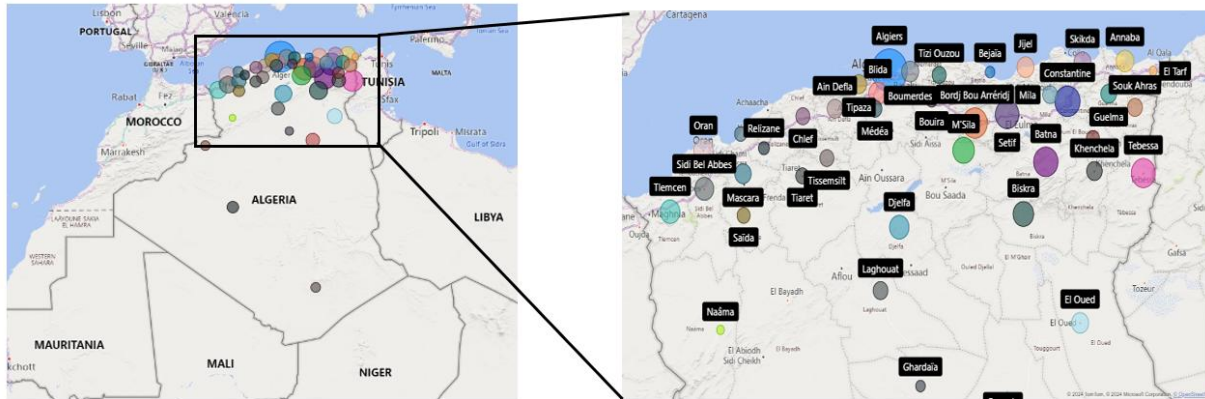


Figure 1. Geographic distribution of Algerian survey participants (n = 478). The size of each colored dot is proportional to the number of participants in that area.

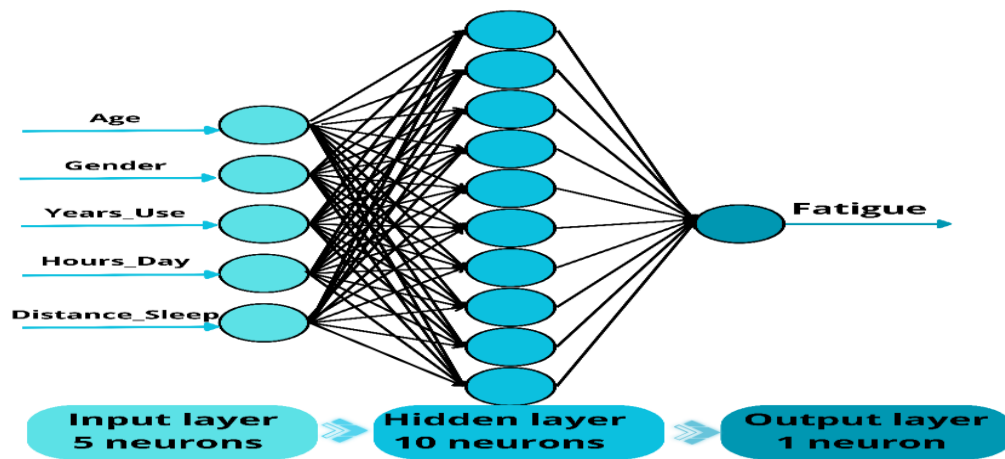


Figure 2. Schematic representation of the proposed ANN model.

While the output variable was the degree of self-reported fatigue, obtained from the health symptoms section of the questionnaire (Figure 2), fatigue frequency was assessed using a five-level Likert scale (never, rarely, sometimes, while using a cell phone, and often).

Data Coding and ANN Model

To enable ANN processing, all input and output variables were converted to numerical codes. For gender, a value of 1 was assigned to male participants and 2 to female participants. For fatigue, the coding was as follows: 1 = never, 2 = rarely, 3 = sometimes, 4 =while using a mobile phone, and 5 = often. Other categorical variables were coded similarly, and a sample of the dataset was used for training and testing the model.

The proposed ANN is a multilayer feedforward network with five input neurons, one hidden layer composed of 10 neurons, and a single output neuron,

Table 1. Summary of the dataset.

Workspace	
Name	Value
data	478×6 double
headers	1×6 cell
hidden_layer	10
mse	0.5993
net	1×1 network
predicted_output	1×143 double
r2	0.0338
raw	479×6 cell
test_data	143×6 double
train_data	335×6 double
train_ratio	0.7000
train_sample	335

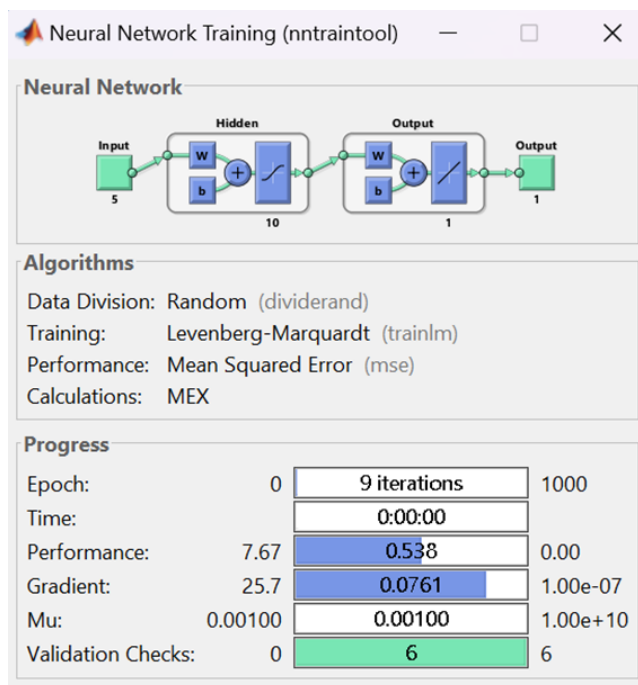


Figure 3. Neural network architecture and training performance.

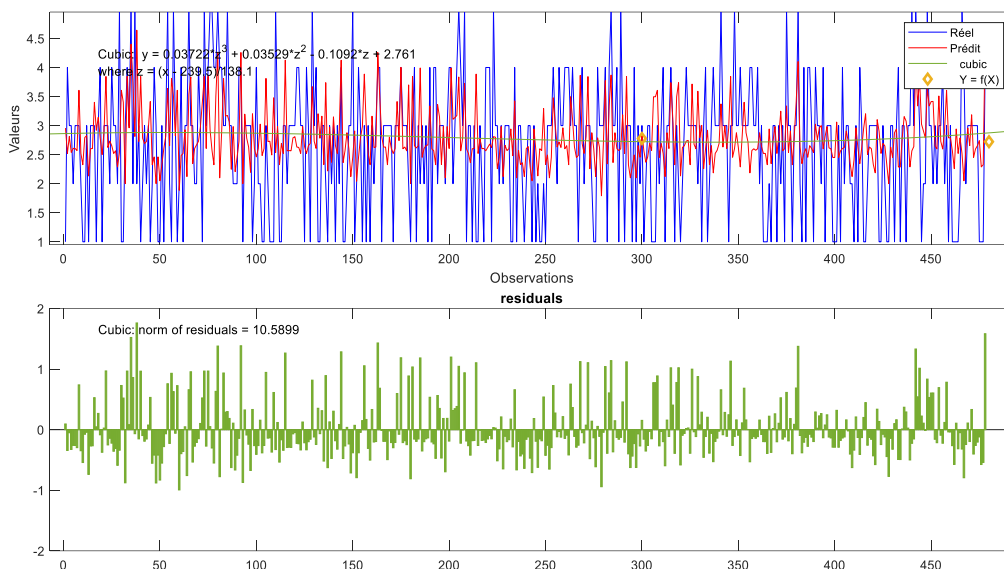
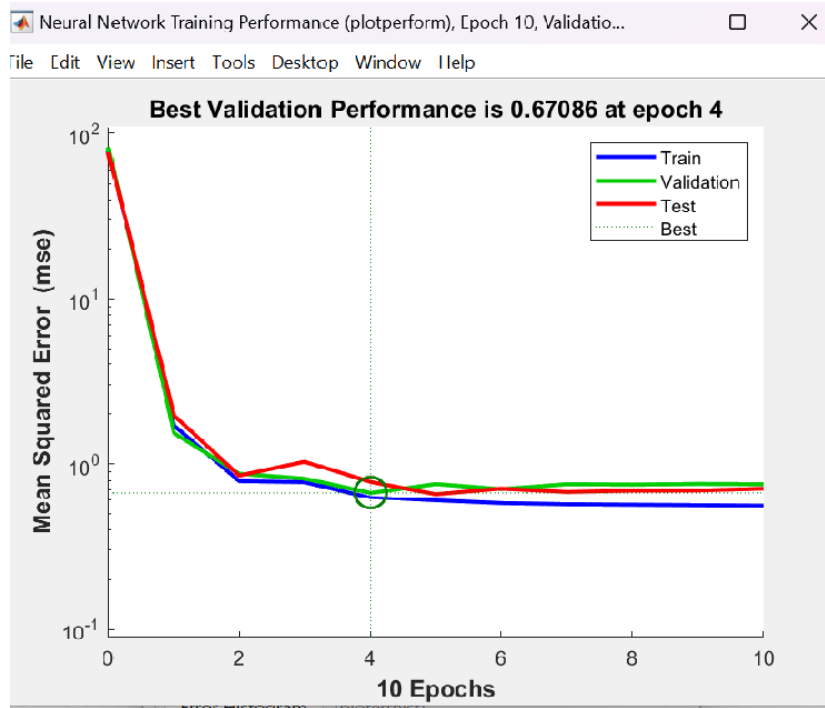


Figure 4. Comparison of actual and predicted fatigue levels with cubic regression fit and residual analysis.

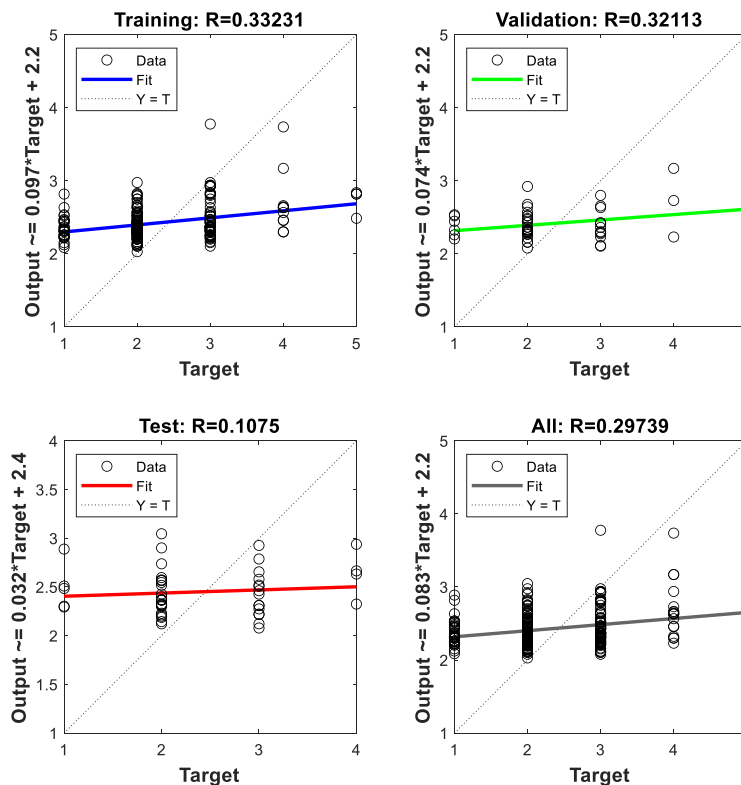
corresponding to the predicted fatigue level (5–10–1 topology) (Figure 2). This architecture was selected after preliminary trials in which several candidate topologies were trained using the same training/validation/test split and the Levenberg–Marquardt algorithm. Model choice was guided by validation mean squared error and the correlation between observed and predicted fatigue.

The Levenberg–Marquardt backpropagation algorithm was chosen. This algorithm is specifically designed for non-linear least-squares problems and is known to provide very fast convergence for small- to medium-sized networks. Model performance was evaluated mainly using the mean squared error (MSE). As illustrated in Figure 3, the network was



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Figure 5. Training, validation, and test performance of the ANN model.



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Figure 6. Regression plots between target and predicted fatigue values for the training, validation, test, and overall datasets.

trained for up to 1,000 iterations. Still, the training stopped automatically after only nine iterations because no further improvement was observed during six consecutive validation checks. This early stopping procedure helped to limit overfitting. The

optimization process is summarized in Table 1, which shows that a total of 478 observations with six variables were processed. Of these, 335 samples (70%) were used for training, and 143 samples (30%) were reserved for testing. The trained model reached

a mean squared error (MSE) of 0.5993 and a low coefficient of determination ($R^2 = 0.0338$).

This suggests that although the network detected some patterns in the data, most of the variability in fatigue scores remained unexplained.

To visualize the model's performance (Figure 4), the observed fatigue scores (blue) were plotted alongside the ANN predictions (red). A cubic regression curve was then fitted to the predicted values (orange line), described by the equation: $y = 0.03722 z^3 + 0.03529 z^2 - 0.1092 z + 2.761$ (where: $z = (x - 239.5)/138.1$). The overall alignment between predicted and observed values suggests that the ANN captures the main trends in fatigue, even though individual predictions show noticeable variability. The lower panel of Figure 4 displays the residuals (green), with a cubic residual norm of 10.5899. This suggests that prediction errors are mostly centered around zero and that no systematic bias is present.

Theoretically, the network's optimization process could run for up to 1 000 iterations to minimize error. In this case, training stopped after 10 iterations, and the best validation score appeared at epoch 4 (MSE = 0.67086) (Figure 5). The small gap between the training, validation, and test curves also suggests that the network did not experience substantial overfitting.

The system provides descriptive statistics for each variable and allows direct comparison of observed fatigue scores with those predicted by the network. In the original dataset, fatigue ranged from 1 ("never") to 5 ("often"), with a mean of 2.65 and a standard deviation of 1.15, indicating substantial variability between participants. By contrast, the predicted values ranged from 1.79 to 4.64, with a mean of 2.80 and a lower standard deviation of 0.49, showing that the predictions were more tightly clustered around the middle of the scale and that the overall range was compressed. This compression of the predicted values (mean 2.80, SD 0.49) relative to the observed scores (mean 2.65, SD 1.15) is a classic sign of underfitting, indicating that the model is not sufficiently complex or lacks informative features to capture the full variability in the data. A cubic model was fitted to the network outputs to provide a smooth approximation of this general trend and an interpolation function. When specific x values were tested (for example, 35, 300, and 480), the corresponding predicted fatigue levels all fell within a narrow band around 2–3, confirming that the model captures the central tendency but underestimates

extreme responses and the observed variability.

Results

Performance Metrics

Model errors were examined using an error histogram including the training, validation, and test samples. Most errors clustered around zero, indicating that predicted fatigue scores were generally close to the observed values and that no strong systematic bias was apparent. The histogram, however, shows that prediction accuracy varied across individuals, consistent with the problem's complexity and the dataset's limited size.

Regression plots were used to visually assess the ANN's predictive performance across the training, validation, test, and overall datasets (Figure 6). In each panel, the observed (target) fatigue scores are plotted against the corresponding predicted values, together with a fitted regression line (solid) and the identity line $Y = T$ (dotted), which represents perfect agreement. In all subsets, the regression slopes are very shallow (training = 0.097, validation = 0.074, test = 0.032, overall = 0.083), indicating only weak linear correspondence between observed and predicted scores. The wide scatter of points around the identity line confirms that the model explains only a small portion of the variance in fatigue and mainly predicts values near the mean, underestimating extreme fatigue levels.

Visual Interface Application

An ANN model was designed and optimized to predict the effect of each input variable on the fatigue level output variable. To make this model usable outside MATLAB, a graphical user interface was designed (Figure 7). Users can enter the main risk factors (age group, gender, phone distance during sleep, years of use, and daily usage time) and obtain an immediate prediction of the fatigue level. The result is displayed as a numerical score and a color indicator ranging from green (low fatigue) to red (high fatigue), making it easy to interpret and support basic preventive advice. Because the model was trained on a relatively small dataset, its predictions should be viewed as a proof of concept that will need further refinement with a larger and more diverse sample. The result is displayed both numerically and with a color-coded indicator, ranging from green (low fatigue) to red (high fatigue). This offers a simple and intuitive way to visualize risk and guide preventive strategies.

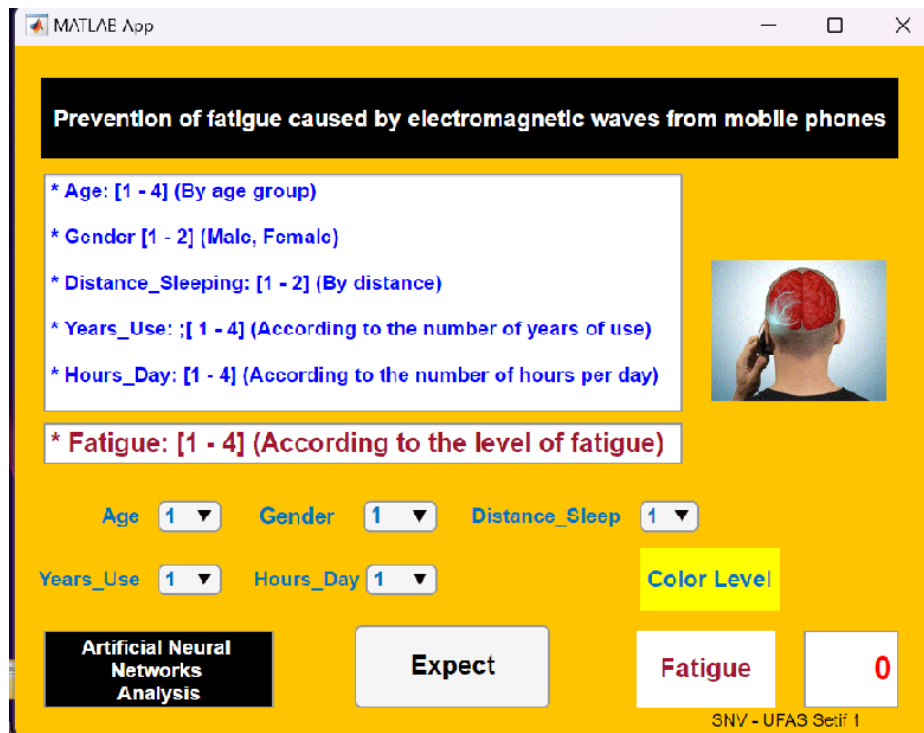


Figure 7. Visual application interface for predicting fatigue levels associated with mobile phone use. Conclusion.

Discussion

This study represents an initial attempt to model fatigue associated with cell phone use using an ANN. The model was able to handle multiple exposure and sociodemographic variables simultaneously and to capture some general trends in the data.

However, its predictive performance remained modest, with a low coefficient of determination and a tendency to compress fatigue scores around the mean. These findings suggest that, with the current set of predictors and sample size, the model should be viewed as a proof of concept rather than a tool for individual risk prediction.

Several limitations must be acknowledged. The analysis relied on self-reported data from a relatively small, cross-sectional sample and included a restricted number of exposure and lifestyle variables. Future studies should incorporate larger and more diverse samples, objective indicators of phone use (for example, screen time logs and usage records directly extracted from the phone), and validated measurement instruments for both fatigue and potential confounders, such as the Chalder Fatigue Scale or Fatigue Severity Scale for fatigue, and tools like the Pittsburgh Sleep Quality Index and the Perceived Stress Scale to better characterize sleep and psychological stress. A longitudinal design would also

be valuable for establishing the temporal relationship between exposure patterns and the development or persistence of fatigue.

From a methodological perspective, further work should compare the present ANN approach with more advanced machine learning models, such as Gradient Boosting and Random Forests, as well as with traditional regression, to determine whether more flexible algorithms can improve predictive performance and calibration. In addition, the use of modern interpretability techniques, such as SHAP (SHapley Additive exPlanations) or permutation importance, could help clarify the relative contribution of each predictor and provide more transparent insights into how model outputs are generated. As wireless technologies continue to evolve and patterns of use change, improved ANN and machine learning models trained on richer, better-characterized datasets may contribute to a more nuanced understanding of fatigue associated with mobile phone use and help inform future public health recommendations.

Conclusion

In summary, the ANN captured broad patterns linking cell phone use-related factors to fatigue, but its predictive accuracy was limited. Under the present conditions, it should be considered an exploratory step that demonstrates feasibility rather than a model suitable for individual-level prediction. Strengthening future studies with larger samples, objective exposure

measures, validated instruments, and comparative modeling may substantially improve performance and enhance the value of machine learning approaches in this area.

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Ethical Approval

Written consent was obtained from all participants, and the study was conducted in accordance with the Declaration of Helsinki.

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Conflicts of Interest

The authors report there are no competing interests to declare.

Declaration of Generative AI and AI-assisted Technologies

During the preparation of this work, the authors used artificial intelligence (ChatGPT 5.1) to improve the linguistic quality of the text. They subsequently reviewed and, where necessary, edited the content and take full responsibility for the publication's content.

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